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Optimal Resource Block Assignment and Power Allocation for D2D-Enabled NOMA Communication

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ABSTRACT A novel joint optimization framework for device-to-device (D2D)-enabled non-orthogonal multiple access (NOMA) networks is proposed. Our objective is to maximize the performance of the D2D communication by jointly optimizing the resource block (RB) assignment and the power allocation, by considering the SIC decoding order of the NOMA-based cellular user equipments (CUEs). We invoke the distributed decision making (DDM) framework to decouple the formulated problem into two sub-problems. For the RB assignment sub-problem with integer variables, we propose a differential evolution (DE) algorithm to obtain the optimal NOMA CUE group and RB assignment for D2D pairs. For power allocation sub-problem with continuous variables and decoding order variables, we first use a heuristic algorithm to optimize the power allocation for NOMA-based CUEs with given D2D power allocation. We prove that the power allocation for the NOMA-based CUEs is the optimal solution. We then invoke the successive convex approximation (SCA) and DE to find the sub-optimal power allocation of the D2D pairs. The numerical results validate the feasibility, fast convergence, and flexibility of the proposed algorithm, and the performance with our algorithm outperforms the conventional OMA technology in terms of energy efficiency and sum rate.

INDEX TERMS DDM, DE, D2D, NOMA, RB assignment, power allocation.

I. INTRODUCTION

Recently, the exponential increase of smart devices and upsurge growth of various mobile applications have largely accelerated the growth of mobile data traffic. As reported by Cisco, the monthly global mobile data traffic will reach 30.6 exabytes by 2020, and this trend will be continuing until 2022 [1]. This exponentially growing data has placed a huge challenge on conventional cellular base stations [2]. In order to cope with those flood data demands, the device-to-device (D2D) communication has been emerged as a

promising solution. In D2D, devices in close proximity are allowed to exchange data directly without the help of cellular base stations (BSs). Due to its short communication range between the transmitter and receiver in a D2D pair, the proximity gain is enhanced, and the offload of the BS is also reduced.

As specified by 3GPP, there are two modes to allow D2D communication coexist with conventional cellular communication: the overlay mode and the underlay mode. In the former one, D2D communications are assigned with dedicated spectrum, which is different from the spectrum allocated for conventional cellular users. However, the dedicated spectrum for D2D users may not be efficiently

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utilized. In the underlay mode, D2D communications share the same spectrum with cellular users, but cannot damage the existing cellular communications. This mode is very similar as the cognitive radio technology [3], where the D2D pairs are viewed as cognitive radio users, and cellular users are viewed as primary users. Although the spectrum efficiency is improved compared with the former one, the mutual interference are imported for both D2D pairs and CUEs. Resource allocation including RB assignment and power allocation is needed to tackle this problem. Somewhat related RB assignment and power allocation problems have been proposed, such as the joint resource allocation and D2D mode selection for single cellular network [4] or the semi-distributed optimization in D2D enabled network [5], [6]. However, existing D2D-enabled systems are usually operating with orthogonal multiple access (OMA) technique, where each RB can be occupied at most one CUE [7]. In order to ensure the minimum QoS level of CUE communication, the massive connectivity, low latency and the diversity quality of service (QoS) requirement for D2D pairs is thus not well supported.

Recently, the non-orthogonal multiple access (NOMA) has emerged as a promising solution to address those aforementioned problems. Unlike OMA technique, NOMA can serve multiple users simultaneously with the same RB by adopting successive interference cancellation (SIC) in decoding at the receiver [8]. Due to its great potential for enhancing the spectral efficiency and providing massive connectivity, NOMA was recommended as one of the promising candidates in future 5G networks [9]. By taking the advantage of both D2D communication and NOMA features, this paper establishes the potential of resource allocation in a D2D enabled NOMA network.

A. RELATED WORKS

1) STUDIES ON D2D COMMUNICATIONS

For D2D communication operating with underlay mode, communications between the BS and CUEs suffer from the interference by those D2D pairs taking the same spectrum. Consequently, resource allocation should be studied to maximize the data rate and ensure the QoS level of the CUEs [10]. In [11], a centralized power allocation was studied in D2D-enabled single cell cellular networks. This work was further extended in [12], where the joint RB assignment and power allocation was investigated. Aiming at reducing the signaling overhead in centralized algorithms, a distributed resource allocation based on stackelberg game was proposed in [13]. In order to obtain the balance between the maximum achievable performance and the signaling overhead, a semi-distributed resource allocation was proposed in D2D enabled single cell network [5], where the RB allocation was realized via the centralized graph-theoretical approach, and the power control was realized via the distributed game theory approach. In our previous work [6], the hybrid centralized-distributed resource allocation for D2D-enabled heterogeneous cellular networks was studied, where the UE

association and RB assignment was realized via genetic algorithm, and the power allocation was realized via stackelberg game.

2) STUDIES ON NOMA

Inspired by the potential benefits of NOMA, some literature have studied the resource allocation by integrating NOMA technique with current networks in different scenarios. In [14], the optimal user scheduling and power allocation for millimeter wave NOMA systems was investigated, and the branch and bound approach was proposed to find the optimal solution. The low-complexity algorithm based on matching theory and successive convex approximation (SCA) was also proposed. In [15], a unified NOMA framework including both power-domain NOMA and code-domain NOMA was studied, and a resource allocation joint with user association was also proposed. In [16], the resource allocation for multi-cell NOMA networks was studied. By taking the quality of experience (QoE) as the objective value, a two-step approach including both RB assignment and power allocation was proposed to find the sub-optimal solution. In [17], the power allocation and beam-forming vectors are jointly optimized to maximize the utility of NOMA based MIMO systems was studied, and SCA algorithm based on first-order approximation and semi-definite programming was proposed to minimize the outage probability. In [18], the joint RB assignment and power allocation for heterogeneous cellular network was studied, and a spectrum allocation based on many-to-one matching was proposed.

B. MOTIVATION AND CONTRIBUTIONS

Inspired by the aforementioned potential benefits of NOMA and D2D, it is natural to investigate the promising application of D2D communication and NOMA techniques for further performance improvement, in term of both spectrum efficiency and massive connectivity. Some literature have already investigated the integration of NOMA technique into D2D communications. In [19], the NOMA technology was applied in a D2D group, where each D2D group contains a transmitter and some NOMA receivers. In order to maximize the system sum rate, the joint sub-channel and power allocation based on iterative optimization was proposed. In [20], the two-hop D2D communication integrated with NOMA technology was proposed, where the NOMA technology was applied at the transmitter to improve the spectrum efficiency. In [21], the D2D and NOMA based cellular network with energy harvesting was investigated, where both D2D pairs and CUEs harvest energy from a hybrid access point (HAP) and an iterative algorithm to find the optimal power control and time allocation was proposed. In [22], the D2D pairs underlay cellular network was studied, and an iterative power allocation algorithm based on Nash bargaining game was proposed. In [23], the joint power control and channel assignment for D2D underlying NOMA networks was investigated, and optimal power control was solved by dual-based iterative algorithm.

It is worth pointing out that when D2D pairs reuse the same RB of NOMA based CUEs, these CUEs will receive different interference from D2D pairs. How to determine the SIC decoding order for those CUEs is much more complicated than that without D2D pairs. To cope with it, some literature have imposed additional constraint SIC decoding order in their optimization models, where the resource allocation for D2D pairs should not destroy the original SIC orders of these NOMA CUEs. Since the resource allocation for D2D pairs and NOMA based CUEs are coupled together, the SIC decoding order is changeable with different resource allocation of D2D pairs, and vice versa. This indicates that whether ensure the original SIC decoding order can obtain the optimal performance is still not very clear. As such, we are more concerned about the resource allocation problem for both D2D pairs and NOMA CUEs simultaneously, where the RB assignment and power control for D2D pairs, the CUE clustering and power control for BSs are jointly optimized in our paper. By formulate the optimization problem, we observe that the joint optimization problem turns out to be a combinatorial non-convex problem, and can be decoupled into a RB assignment sub-problem with integer variables and a power allocation sub-problem with continuous variables. Considering bio-inspired algorithm have become increasingly popular in solving combinatorial optimization problems, we propose to apply the distributed decision making (DDM) framework and differential evolution algorithm (DE) to find the joint optimal solution. The main contributions of this paper are summarized as follows:

- We propose a novel joint optimization for D2D enabled NOMA communication problem, where the RB assignment and power allocation and SIC decoding order for NOMA based CUEs are jointly considered and optimized. We apply the DDM framework to decouple it into two problems: the RB assignment sub-problem and power allocation sub-problem.
- For solving the RB assignment sub-problem, we develop an optimization framework based on adaptive DE algorithm, where D2D RB assignment, CUE clustering is represented as an individual in DE. We design appropriate individual encoding scheme to satisfy the RB assignment constraint. We also propose individual evolution methods in correspondence with the encoding scheme to reach the optimal solution.
- For solving the power allocation sub-problem, we first propose a heuristic algorithm to find power allocation of NOMA based CUEs with fixed D2D power allocation. We prove that the power allocation is the optimal solution for these CUEs. By transform the problem into a convex optimization, We further apply the sequential convex programming (SCA) and DE to iteratively update the power allocation of D2D pairs.
- Extensive numerical results show that the proposed power allocation optimization algorithms achieve nearly the same performance. The proposed framework outperforms the conventional OMA networks. Moreover,

we show that the performance of D2D communications can be improved by increasing the number of RBs and maximum allocated power.

The rest of this paper is organized as follows. In Section II, we present the system model and problem formulation. Section III proposes the joint optimization framework based DDM. Section IV presents the DE-based RB assignment for D2D pairs and NOMA based CUEs. Section IV proposes the power allocation algorithm for both BS and D2D pairs. Section V presents numerical results and Section VI highlights our conclusions.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. SYSTEM MODEL

We consider a D2D-enabled single cell b with multiple CUEs and D2D pairs. We denote the set of active CUEs as $\mathcal{N} = \{1, 2, \dots, N\}$ and the set of active D2D pairs as $\mathcal{D} = \{1, 2, \dots, D\}$. The d_{th} D2D pair ($d \in \mathcal{D}$) consists of the D2D transmitter $d_T \in \mathcal{D}_T$ and D2D receiver $d_R \in \mathcal{D}_R$, where $\mathcal{D}_T = \{1_T, 2_T, \dots, D_T\}$ and $\mathcal{D}_R = \{1_R, 2_R, \dots, D_R\}$. The set of all UEs of the network is denoted as $\mathcal{U} = \mathcal{N} \cup \mathcal{D}_T \cup \mathcal{D}_R$. We denote the set of available set of orthogonal resource blocks (RBs) as $\mathcal{M} = \{1, 2, \dots, M\}$.

To specify the RB assignment of CUE, we define v_n^m as its RB assignment indicator, which is a binary variable. If $v_n^m = 1$, it indicates that n th CUE ($n \in \mathcal{N}$) is associated with the m th resource block, and $v_n^m = 0$ ($m \in \mathcal{M}$) if otherwise. Different from existing works, we assume multiple different CUEs can reuse the same RB via NOMA communication to improve the spectrum efficiency. And denote these CUEs allocated with the m th RB as \mathcal{N}_m , and assume each CUE can be allocated at most one RB, thus $\mathcal{N} = \mathcal{N}_1 \cup \mathcal{N}_2 \cup \dots \cup \mathcal{N}_M$ and $\mathcal{N}_i \cap \mathcal{N}_j = \emptyset$ for $i \neq j$. For simplicity, we ignore shadowing and consider Rayleigh fading only. As an example, Fig. 1 illustrates a D2D-enabled system with 4 D2D pairs 8 CUEs and 8 RBs. With NOMA technology, these CUEs can be clustered into 3 NOMA groups, and only occupy 3 RBs, thus to improve the performance of D2D pairs.

The NOMA based transmission requires to apply the superposition coding (SC) technique at the BS and SIC technique at the CUEs using the same RB. Based on the NOMA principle, the superposition coded symbol x_m to be transmitted by the BS over RB m is given by

$$x_m = \sum_{n \in \mathcal{N}} v_n^m \sqrt{P_n^m} s_n^m \quad (1)$$

And the received signal at CUE n on the m -th RB is given by

$$y_n^m = \underbrace{h_{b,n}^m v_n^m \sqrt{P_n^m} s_n^m}_{\text{desired signal}} + \underbrace{\zeta_{b,n}^m}_{\text{Noise}} + \underbrace{h_{b,n}^m \sum_{j \in \mathcal{N}/n} v_j^m \sqrt{P_j^m} s_j^m}_{\text{Interference from NOMA users}} + \underbrace{\sum_{d \in \mathcal{D}} v_{d,n}^m \sqrt{P_d} s_d h_{d,n}^m}_{\text{Interference from D2D users}} \quad (2)$$

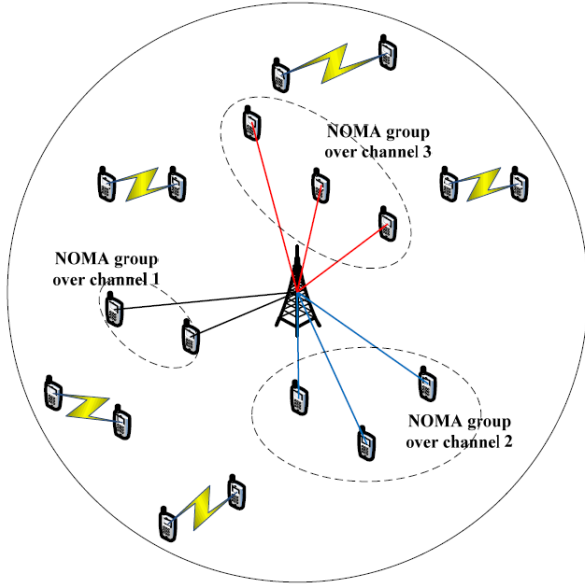


FIGURE 1. Illustration of D2D-enabled NOMA communication model.

NOMA systems exploit the power domain for multiple access, where different users are served at different power levels. For illustration, assume CUE n desires to decode and remove interference from the superposition signal of CUE j via SIC on the m th RB. The interference cancellation is successful if the CUE n 's received SINR for the CUE j 's signal is larger or equal to the received SINR of CUE j for its own signal [14], [16]. Therefore, the condition of SIC decoding order between the i th and j th CUE is given by

$$\frac{v_n^m |h_{b,n}|^2 P_n^m}{\sum_{i=1, i \neq k}^N v_i^m |h_{b,n}|^2 P_i^m + \sum_{d \in \mathcal{D}} v_d^m P_d h_{d,n}^m + \sigma^2} \geq \frac{v_k^m |h_{b,k}|^2 P_k^m}{\sum_{i=1, i \neq k}^N v_i^m |h_{b,k}|^2 P_i^m + \sum_{d \in \mathcal{D}} v_d^m P_d h_{d,k}^m + \sigma^2} \quad (3)$$

Furthermore, we define $x_{i,j}^m$ as the SIC condition indicator of i and j on the m th RB. If $x_{i,j}^m = 1$, it indicates that the i th CUE can cancel the interference of CUE the j th CUE ($i, j \in \mathcal{N}, i \neq j$) on the m th RB, and $x_{i,j}^m = 0$ ($m \in \mathcal{M}$) if otherwise.

Therefore, according to SIC condition, the received SINR of the n th CUE on the m th RB is given by

$$\gamma_n^m = \frac{v_n^m |h_{b,n}|^2 P_n^m}{\sum_{i=1, i \neq n}^N v_i^m x_{i,n}^m |h_{b,n}|^2 P_i^m + \sum_{d \in \mathcal{D}} v_d^m P_d h_{d,n}^m + \sigma^2}. \quad (4)$$

We then formulate the received SINR of the d th D2D on the m th RB as

$$\gamma_d^m = \frac{v_d^m |h_{d,d}|^2 P_d}{\sum_{i=1}^N v_i^m |h_{b,d}|^2 P_i^m + \sum_{j \in \mathcal{D}/d} v_j^m P_j h_{j,d}^m + \sigma^2}. \quad (5)$$

B. PROBLEM FORMULATION

The target of this paper is to maximize the overall obtained rate among all D2D pairs while still guarantee the rate requirement of all CUEs. To achieve this, an optimization algorithm is required to perform the optimal channel assignment, power allocation and SIC decoding. We therefore present the joint optimization problem as

$$\max_{\mathbf{v}, \mathbf{P}} \sum_d \sum_m \log(1 + \gamma_d^m) \quad (6)$$

$$\text{s.t.} \sum_n \sum_m P_n^m \leq P_b^{\max}, \quad (6a)$$

$$\sum_m \log(1 + \gamma_n^m) \geq r_n, \quad \forall n \in \mathcal{N} \quad (6b)$$

$$\sum_m v_n^m \leq 1, \quad (6c)$$

$$\sum_m v_d^m \leq 1, \quad (6d)$$

$$0 \leq P_d \leq P_d^{\max}, \quad \forall d \in \mathcal{D} \quad (6e)$$

$$v_n^m, v_d^m, x_{i,j}^m \in \{0, 1\}, \quad \forall n, i, j \in \mathcal{N}, d \in \mathcal{D}, m \in \mathcal{M}. \quad (6f)$$

The constraint in (6a) indicates that the maximum power constraint the BS, and the constraint (6b) indicates the minimum rate requirement of each CUE. The constraints (6c) and (6d) indicate each D2D pair or CUE can only occupy only one RB. As can be observed, the optimization problem in (6a) contains integer variables $v_d^m, v_n^m, x_{i,j}^m$ and continuous variables P_d and P_n^m . Moreover, the objective function is non-convex. Instinctively, this optimization problem is in the form of mixed integer non-linear programming (MINLP) problem, which is generally NP-hard and there is no systematic and computational efficient approach to solve this problem optimally. In the following sections, we will apply the DDM framework to decouple it into two sub-problems, and develop a low complexity algorithm based on DE to find the optimal solution.

III. OPTIMIZATION FRAMEWORK

In order to solve the above MINLP problem, a problem decomposition framework based on distributed decision making (DDM) [24] theory is presented in this section. The original complex problem after decomposition is grouped into two layers: the top layer model and bottom layer model. Generally, the top layer model has a higher priority and provides a top-to-bottom information to guide the optimization process of the bottom layer model. After that, the bottom layer optimizes continuous objective functions and feeds its optimal solution back to the top layer model.

Since the performance highly relies on the NOMA CUEs, it is important to determine the integer variables first. After that, the optimal power allocation for each connection can be determined. Therefore, the actual decomposition framework based on DDM is illustrated in Fig. 2. In this framework, we denote the top layer model as *the RB assignment problem*,

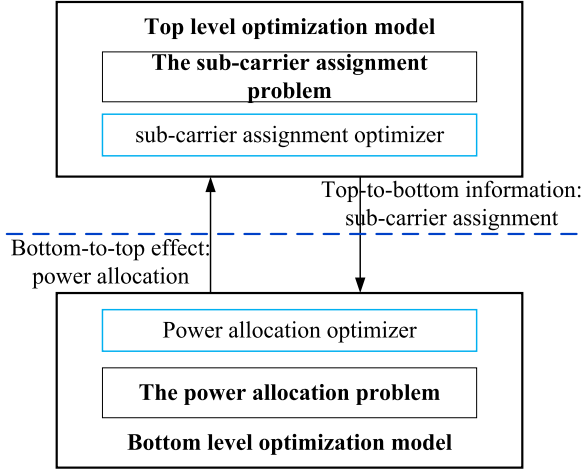


FIGURE 2. Joint optimization framework based on DDM.

which is responsible for optimizing the integer variables v_d^m and v_n^m , and is given by

$$\max_v \sum_d \sum_m \log(1 + \gamma_d^m) \quad (7)$$

$$\text{s.t.} \sum_m \log(1 + \gamma_n^m) \geq r_n, \quad \forall n \in \mathcal{N} \quad (7a)$$

$$\sum_m v_n^m \leq 1, \quad (7b)$$

$$\sum_m v_d^m \leq 1, \quad (7c)$$

$$v_n^m, v_d^m \in \{0, 1\}, \quad \forall n \in \mathcal{N}, d \in \mathcal{D}, m \in \mathcal{M}. \quad (7d)$$

We denote the bottom layer model as *the power allocation problem*, which is responsible for optimizing the decoding order $x_{i,j}^m$, and the continuous variables P_d and P_n^m , and is given by

$$\max_p \sum_d \sum_m \log(1 + \gamma_d^m) \quad (8)$$

$$\text{s.t.} \sum_n \sum_m P_n^m \leq P_b^{\max}, \quad (8a)$$

$$\sum_m \log(1 + \gamma_n^m) \geq r_n, \quad \forall n \in \mathcal{N} \quad (8b)$$

$$0 \leq P_d \leq P_d^{\max}, \quad \forall d \in \mathcal{D} \quad (8c)$$

$$x_{i,j}^m \in \{0, 1\}, \quad \forall i, j \in \mathcal{N}, m \in \mathcal{M}. \quad (8d)$$

IV. RB ASSIGNMENT FOR THE TOP LEVEL MODEL

In this section, we present the optimization for the RB assignment for both D2D pairs and CUEs. We assume the power allocation for each D2D pair and the CUEs are fixed.

As shown in (7a), the formulated problem is a non-convex optimization problem due to the existence of objective function and the constraint (7a). Since the problem size increases exponentially with increasing the number of D2D pairs and RBs. It is not feasible to solve this problem by an exact algorithm with a huge problem space size. In order to cope

with it, many bio-inspired algorithms have been proposed, such as genetic algorithm (GA) [25], particle swarm optimization (PSO), differential evolutionary (DE) [26], and artificial bee colony (ABC) [27]. By simulating the intelligent behavior of natural system in searching the optimal solution, these algorithms have been widely applied for various real world NP-hard problems. Among them, it has shown that DE is very suitable to optimize problems with high dimensional variables comparing with other bio-inspired algorithms. We therefore take DE as the optimizer to find an optimal RB assignment. In order to tailor DE for a particular problem, the following 4 operations should be designed: 1) initialization, 2) mutation, 3) crossover, and 4) selection.

The first issue in designing DE is how to encode the solution of a problem, and generate an initial population based on the designed encoding scheme. In our algorithm, we denote the initial population of DE as $\mathcal{Q} = \{\Gamma^q\}_{q=1}^Q = \{D^q, C^q\}_{q=1}^Q$, which contains Q individuals, where D^q is a potential solution of the RB assignment for D2D pairs and C^q is a potential solution of the RB assignment for CUEs. We illustrate these two integer-based matrices as follows:

- 1) D2D RB assignment matrix D^q is

$$D^q = [d_1^q, \dots, d_D^q], \quad (9)$$

where the element d_i^q ($1 \leq d_i^q \leq M, 1 \leq i \leq D$) indicating the RB assignment of the i th D2D pair.

- 2) CUE RB assignment matrix C^q is

$$C^q = [c_1^q, \dots, c_N^q], \quad (10)$$

where the element c_i^q ($1 \leq c_i^q \leq M, 1 \leq i \leq N$) indicating the RB assignment of the i th CUE.

Note that this encoding scheme always satisfies the RB allocation constraint, where each D2D pair or CUE occupies at most one RB. Besides that, for CUEs assigned with the same RB in C^q , these CUEs will be formed as NOMA groups. Take figure 1 as an example, one encoding example for the D2D RB assignment in this system is $D^q = [1, 2, 3, 2, 1]$, which indicates that the 1_{st} and 5_{th} D2D pair occupy the 1_{st} RB, and the 2_{nd} and 4_{th} D2D pair occupy the 2_{nd} RB. One example of the RB assignment for CUEs is encoded as $C^q = [1, 1, 2, 2, 2, 3, 3, 3]$, which indicates that the 1_{st} and the 2_{nd} CUE occupy the 1_{st} RB, and formed as the a NOMA group, the 3_{rd}, 4_{th}, and 5_{th} CUE occupy the 2_{nd} RB, and also formed as a NOMA group. Based on these two matrices, we generate an initial population contain Q with Q individuals. In order to explore diversity, the element of each individual is randomly generated.

Another important issue in designing DE is to apply the mutation and crossover operation for offspring production. Unlike conventional DE using fixed crossover constant cr and mutation control parameter F , the self-adaptive DE algorithm is applied, where these values are self-adapted for each individual corresponding with iterations. Denote three randomly selected individuals from previous population as Γ^l , Γ^c , and Γ^u , and the corresponding fitness value for these individuals as f_l, f_c , and f_u , where the fitness value is denoted as

the objective value according to the individual representation. Besides, we assume a sorting operation is performed after selection, and the fitness of these three individuals satisfies $f_l \leq f_c \leq f_u$. Based on these assumption, a donor individual after mutation can be given by

$$V_i = X_b + F_i(\Gamma^u - \Gamma^c) \quad (11)$$

where F_i is the scalar parameter. Denote the upper and low bound of F_i as F_L and F_U . We updated F_i as

$$F_i = F_L + (F_U - F_L) \frac{f_c - f_l}{f_u - f_l} \quad (12)$$

Crossover helps to enhance the potential diversity of the population and is conducted after mutation. In our paper, the crossover probability cr_i is given by

$$cr_i = 0.1 + 0.6 \frac{f_i - f_{min}}{f_{max} - f_{min}} \quad (13)$$

where f_{max} and f_{min} are the maximum and minimum fitness values of the population accordingly.

With these designed key issues of DE operations, such as individual encoding, mutation and crossover, we therefore illustrate the detail of the DE based RB assignment in Algorithm 1, where T is the given number of generations, Q is the population size. $\{P_d^m | \forall d \in \mathcal{D}\}$ and $\{P_n^m | \forall n \in \mathcal{N}\}$ are the given power allocation for D2D pairs and CUEs, we assume these power allocation are fixed during this algorithm.

Remark 1: Let $O(f)$ be the complexity of fitness evaluation, the complexity of algorithm 1 is $O(TQ(O(f) + Q))$.

Proof: Since the computational complexity is dominated by the complexity in the fitness evaluation, which has to be evaluated G times in each iteration. Apart from this, this algorithm also depends on other factors, which are difficult to clearly enumerate, such as strategies to generate new population, and the tolerance allowable for cumulative changes in fitness values [28]. Excluding these parameters, the total complexity of algorithm 1 is $O(TQ(O(f) + Q))$. \square

V. POWER ALLOCATION FOR THE BOTTOM LEVEL MODEL

In this section, we present the optimization for the power allocation for both D2D pairs and CUEs. We assume the RB assignment for each D2D pair and the CUEs are obtained from the top level model.

A. POWER ALLOCATION FOR THE NOMA CUES

As shown in (8a), the formulated problem is still a MINLP problem due to the existence of objective function and the variable $x_{i,j}^m$. Intuitively, this problem can be solved by bio-inspired algorithm, such as DE or GA. However, due to the fact the optimization variables $x_{i,j}^m$, P_n^m and P_d in (8a) are coupled together, it is very hard to encode them randomly while still satisfy the constraints, which may need lots of iterations to find sub-optimal solutions. We therefore first presents how

Algorithm 1 RB Assignment Based on DE

Input: The maximum iteration T , the power allocation of D2D pairs $\{P_d^m | \forall d \in \mathcal{D}\}$ and the power allocation of CUEs $\{P_n^m | \forall n \in \mathcal{N}\}$

Output: The RB assignment of D2D pairs $\{v_d^m | \forall d \in \mathcal{D}\}$ and the RB assignment of CUEs $\{v_n^m | \forall n \in \mathcal{N}\}$

Set $t = 1$

Generate initiation population Q according to the designed encoding scheme

Calculate the fitness value for each individual in Q with the fixed power allocation $\{P_d^m | \forall d \in \mathcal{D}\}$ and $\{P_n^m | \forall n \in \mathcal{N}\}$

while $t \leq T$ **do**

Set $Q' = \Phi$ and $i = 1$

while $i \leq Q$ **do**

Randomly select three individuals Γ^l , Γ^c , and Γ^u from Q and sorting them such that $f_l \leq f_c \leq f_u$

Perform mutation operation to generate a individual Γ_t^i according according (11)

Calculate the crossover probability cr_i according to (13)

Crossover Γ_t^i with Γ^i with the probability cr_i

$Q' = Q' \cup \{\Gamma_t^i\}$

Calculate fitness value for individual Γ_t^i with the fixed power allocation $\{P_d^m | \forall d \in \mathcal{D}\}$ and $\{P_n^m | \forall n \in \mathcal{N}\}$

$i = i + 1$

end

$t = t + 1$

Replace the individuals with low fitness values in population Q with the children in offspring Q'

end

Return the fittest individual in Q

to find the optimal power allocation of CUEs and SIC orders with the given P_d , and simplify the optimization problem as

$$\max_p \sum_d \sum_m \log(1 + \gamma_d^m) \quad (14)$$

$$\text{s.t.} \sum_n \sum_m P_n^m \leq P_b^{\max}, \quad (14a)$$

$$\sum_m \log(1 + \gamma_n^m) \geq r_n, \quad \forall n \in \mathcal{N} \quad (14b)$$

$$x_{i,j}^m \in \{0, 1\}, \quad \forall i, j \in \mathcal{N}, m \in \mathcal{M}. \quad (14c)$$

By combing (5) into (14a), the objective function is derived as

$$\sum_d \log \left(1 + \frac{v_d^m |h_d|^2 P_d}{\sum_{i=1}^N v_i^m |h_{b,d}|^2 P_i^m + \sum_{j \in \mathcal{D}/d} v_j^m P_j h_{j,d}^m + \sigma^2} \right) \quad (15)$$

As can be observed from (21), it is a decreasing function with P_n^m ($\forall n \in \mathcal{N}$). In order to maximize the objective value, power allocation for each CUE should be as small as possible. Besides that, power allocation for each CUE should also satisfy the rate constraint defined in (14b), whereas data rate constraint for each CUE is a incremental function of P_n^m ($\forall n \in \mathcal{N}$). Combining (21) and (14b), the minimum power should be set as the minimum power to satisfy the data rate, and can be derived as

$$P_n^m = (2^{r_n} - 1) \times \frac{\sum_{i=1}^N v_i^m x_{i,n}^m |h_{b,n}|^2 P_i^m + \sum_{d \in \mathcal{D}} v_d^m |h_{d,n}^m|^2 P_d + \sigma^2}{v_n^m |h_{b,n}|^2} \quad (16)$$

Since all variables in (16) are given except the decoding variable $x_{i,n}^m$ and the power allocated for other NOMA CUEs P_i^m . Besides that, by analyzing the (3), the SIC decoding order between NOMA CUE n and j can be derived as

$$\frac{|h_{b,n}|^2}{|h_{b,k}|^2} \geq \frac{\sum_{d \in \mathcal{D}} v_d^m P_d h_{d,n}^m + \sigma^2}{\sum_{d \in \mathcal{D}} v_d^m P_d h_{d,k}^m + \sigma^2} \quad (17)$$

From (17), it is observed that SIC decoding order only relates with the power allocation of D2D pairs. This indicates that when the power allocation of D2D pairs are given, the SIC decoding order for any two NOMA CUEs can be obtained, and thus the decoding variables $x_{i,n}^m$ can also be obtained in (16).

With this decoding order of any two NOMA CUEs in a NOMA group, the decoding order of a whole NOMA group can also be obtained by any sorting algorithm. Denote N_m the NOMA group of \mathcal{N}_m after decoding order sorting. We assume CUEs in N_m have decreasing decoding order, such that for any two CUEs $i, j \in N_m$, ($i \neq j$), if $i < j$, their decoding order satisfies

$$x_{i,j} = \begin{cases} 1 & \text{if } i < j, \\ 0 & \text{otherwise.} \end{cases} \quad (18)$$

Combining (18) and (16), the minimum power of the n th CUE of N_m is derived as

$$P_n^m = \frac{2^{r_n} - 1}{v_n^m |h_{b,n}|^2} \times \begin{cases} \sum_{d \in \mathcal{D}} v_d^m |h_{d,n}^m|^2 P_d + \sigma^2 & \text{if } n = 1, \\ P_{NOMA} + \sum_{d \in \mathcal{D}} v_d^m |h_{d,n}^m|^2 P_d + \sigma^2 & \text{otherwise.} \end{cases} \quad (19)$$

where $P_{NOMA} = \sum_{i < n, i \in N_m} |h_{b,i}|^2 P_i^m$ is the interference of NOMA CUEs with larger SIC decoding order than the n th CUE.

Theorem 1: The obtained power allocation by (19) is the optimal solution of (14a) with fixed D2D power allocation P_d ($\forall d \in \mathcal{D}$).

Proof: We prove it by contradiction.

Assuming there exists a P_n^{m*} , such that P_n^{m*} is an optimal solution for the n th CUE and $P_n^{m*} \neq P_n^m$. We denote the objective function with P_n^{m*} and P_n^m as $f(P^*)$ and $f(P)$ respectively.

Assuming that $P_n^{m*} > P_n^m$, due to that fact the objective function in (14a) is a decreasing function of P_n^m , if P_n^m is increased to P_n^{m*} , $f(P^*) < f(P)$. This contradicts the assumption that P_n^{m*} is an optimal solution of (14).

Assuming that $P_n^{m*} < P_n^m$, due to the fact that P_n^m is the minimum allocated power to satisfy the data rate requirement, if P_n^m is reduced to P_n^{m*} , the constraint of (14b) cannot be satisfied. This contradicts the assumption that P_n^{m*} is a feasible solution of (14). \square

Algorithm 2 Power Allocation for NOMA CUEs

Input: The RB assignment of CUEs $\{v_n^m | \forall n \in \mathcal{N}\}$,

the RB assignment of D2D pairs $\{v_d^m | \forall d \in \mathcal{D}\}$,

the power allocation of D2D pairs $\{P_d | \forall d \in \mathcal{D}\}$

Output: The power allocation of CUEs $\{P_n^m | \forall n \in \mathcal{N}\}$

for $m = 1 \dots M$ **do**

$\mathcal{N}_m = \{n | n \in \mathcal{N}, v_n^m = 1\}$

 Obtain the SIC decoding order for any two CUEs in

\mathcal{N}_m

 Sort \mathcal{N}_m in descending decoding order with fast sorting algorithm and obtain N_m

for $j = 1 \dots |N_m|$ **do**

 Calculate P_j^m according to (19)

end

end

Remark 2: The time complexity of algorithm 2 is $O(M(O(|N_m| \log(|N_m|)) + |N_m|))$.

Proof: The computational complexity is dominated by the complexity in sorting the decoding order of each NOMA group N_m ($\forall m \in \mathcal{M}$). Since the fast sorting algorithm is applied, its complexity is $O(|N_m| \log(|N_m|))$. Apart from this, this algorithm needs to calculate P_j^m for $|N_m|$ times for each RB. Therefore, the total complexity of algorithm 2 is $O(M(O(|N_m| \log(|N_m|)) + |N_m|))$. \square

B. POWER ALLOCATION FOR THE D2D PAIRS

With **Algorithm 2**, the power allocation for both D2D pairs and CUEs can be simplified as a optimization problem with only D2D power allocation variables, and is formulated as

$$\max_P \sum_d \sum_m \log(1 + \gamma_d^m) \quad (20)$$

$$\text{s.t. } 0 \leq P_d \leq P_d^{\max}, \quad \forall d \in \mathcal{D} \quad (20a)$$

This problem is still a non-convex problem due to the fact it has a difference of convex (d.c.) structure in the objective function, which is given by

$$\begin{aligned} & \sum_d \sum_m \log(1 + \gamma_d^m) \\ &= \sum_d \sum_m \log(I_d + v_d^m |h_d|^2 P_d) - \sum_d \sum_m \log(I_d) \end{aligned} \quad (21)$$

where

$$I_d = \sum_{i=1}^N v_i^m |h_{b,d}|^2 P_i^m + \sum_{j \in \mathcal{D}/d} v_j^m P_j^m h_{j,d}^m + \sigma^2, \quad (22)$$

is the interference on the d th D2D pair. For a non-convex optimization problem, it is difficult to find the optimal solution. However, by approximating the lower bound of the non-convex function, we can utilize the successive convex approximation (SCA) method to solve the power allocation of D2D pairs. According to [18], the following inequality for γ_d^m can be given by

$$\log(1 + \gamma_d^m) \geq \alpha_d^m \log \gamma_d^m + \beta_d^m \quad (23)$$

where α_d^m and β_d^m are defined as

$$\alpha_d^m = \frac{\hat{\gamma}_d^m}{1 + \hat{\gamma}_d^m} \quad (24)$$

and

$$\beta_d^m = \log(1 + \hat{\gamma}_d^m) - \frac{\hat{\gamma}_d^m}{1 + \hat{\gamma}_d^m} \log \hat{\gamma}_d^m \quad (25)$$

respectively. The equality of (23) is satisfied when $\gamma_d^m = \hat{\gamma}_d^m$.

As such, the lower bound of the objective function $\sum_d \log(1 + \gamma_d^m)$ is obtained as

$$\sum_d \sum_m \log(1 + \gamma_d^m) \geq z(P_d) \quad (26)$$

where $z(P_d)$ is defined as

$$z(P_d) = \sum_d \sum_m (\alpha_d^m \log \gamma_d^m + \beta_d^m) \quad (27)$$

To transform it to a concave function, we further set $P_d = 2^{\hat{P}_d}$, a new optimization problem can be obtained from (21) and (29) as follows

$$\max_P z(\hat{P}_d) \quad (28)$$

$$\text{s.t. } 0 \leq 2^{\hat{P}_d} \leq P_d^{\max}, \quad \forall d \in \mathcal{D} \quad (28a)$$

Proposition 1: The rewritten optimization problem in (28a) is a convex optimization problem.

Proof: Combing (5) into (28a), we can obtain

$$\begin{aligned} z(2^{\hat{P}_d}) &= \sum_{d \in \mathcal{D}} \sum_{m \in \mathcal{M}} \alpha_d^m \log(v_d^m v_d^m |h_{b,d}|^2 2^{\hat{P}_d}) \\ &\quad - \sum_{d \in \mathcal{D}} \sum_{m \in \mathcal{M}} \log \left(\sum_{i=1}^N v_i^m |h_{b,d}|^2 P_i^m \right. \\ &\quad \left. + \sum_{j \in \mathcal{D}/d} v_j^m 2^{\hat{P}_j} h_{j,d}^m + \sigma^2 \right) \end{aligned} \quad (29)$$

Since the log-sum-exp function is convex, we thus conclude that the optimization problem in (28a) is a standard convex optimization problem. \square

Once the optimal solution is obtained, we need to transform it back into the P -space as $P_d = 2^{\hat{P}_d}$. Besides that, we should

iteratively update the power allocation to tighter the lower bound of (28a) until convergence. Algorithm 2 illustrates the details of the proposed power allocation algorithm. First, a feasible power allocation for each D2D pair is initialized. And then, the power allocation is updated in each iteration. In this algorithm, we first calculate the gap of the values of γ_d^m between two adjacent steps. This algorithm is terminated until the gap is lower than the predefined threshold T_{th} .

Algorithm 3 D2D Power Allocation Based on SCA

Initialization

Initialize the threshold T_{th} and the maximum iteration times T_{max}

Set iteration index $t = 0$, $\alpha_d^{m(0)} = 1$, $\beta_d^{m(0)} = 0$

$\forall d \in \mathcal{D}, \forall m \in \mathcal{M}$

Initialize a feasible power allocation P_d

Obtain the optimal power allocation P_n^m in corresponding to P_d using algorithm 2

Update $\gamma_d^{m(0)}$ with P_d and P_n^m

while (convergence is False) and ($t \leq T_{max}$) **do**

$t = t + 1$

Set $\hat{\gamma}_d^{m(t)} = \gamma_d^{m(t-1)}$

Update $\alpha_d^{m(t)}$ and $\beta_d^{m(t)}$ with $\hat{\gamma}_d^{m(t)}$ according to (24) and (25)

Solve the optimization problem in (28a) and obtain the optimal solution as \hat{P}_d

$P_d = 2^{\hat{P}_d}$

Obtain the optimal power allocation P_n^m in corresponding to P_d using algorithm 2

Calculate $\gamma_d^{m(t)}$ with P_d and P_n^m

if $|\gamma_d^{m(t)} - \gamma_d^{m(t-1)}| \geq T_{th}$ **then**
| convergence = False

else

| convergence = True

end

end

Theorem 2: The proposed algorithm 2 for power allocation is guaranteed to converge.

Proof: Denote \hat{P}_d^t ($\forall d \in \mathcal{D}$) as the optimal solution of the convex problem of (28a) in the t -th iteration, where the SINR value of the d th D2D pair is defined as $\gamma_d^{m(t)}$. Let $P_d^t = 2^{\hat{P}_d^t}$. Let $f(P_d^t) = \sum_d \sum_m \log(1 + \gamma_d^{m(t)})$, we obtain the following inequalities

$$f(P_d^t) = z(2^{\hat{P}_d^t}) \leq z(2^{\hat{P}_d^{t+1}}) \leq f(P_d^{t+1}) \quad (30)$$

The first equality holds because α_d^m and β_d^m are calculated based on $\hat{\gamma}_d^m$, which means the bound is tight; the second inequality holds because \hat{P}_d^{t+1} is the optimal solutions of (28a) for the $t + 1$ -th iteration; the third inequality holds because $z(2^{\hat{P}_d^{t+1}})$ is the lower bounds of $f(P_d^{t+1})$. Therefore, from (30), it is known that the value of $f(P_d^t)$ increases after each iteration. Due to the fact the value of $f(P_d^t)$ is upper bounded due to limited spectrum resources, algorithm 3 can finally converge to the optimal power allocation. \square

Theorem 3: The convergent solution of algorithm 3 is a first-order optimal solution of the problem in (21), which also satisfies KKT conditions.

Proof: We denote the power allocation solution of algorithm 3 as P_d^* . Due to the fact that P_d^* is also the solution of (28a), we can conclude that P_d^* must satisfy KKT condition of (28a). Since (28a) and (21) have the same constraints but different objective function. However, when algorithm 2 converges, the objectives of (28a) and (21) are equal. Thus, P_d^* also satisfies the KKT condition of (21). \square

In order to reduce the complexity in convex optimization, we further propose a heuristic algorithm based DE algorithm to find an sub-optimal D2D power allocation. The population $\mathcal{Q} = \{P^q\}_{q=1}^Q$ contains Q individuals, where P^q represents the q th individual of population \mathcal{Q} ,

$$P^q = [P_1^q, \dots, P_D^q], \quad (31)$$

where the element $1 \leq P_i^q \leq P_d^{max}$, $1 \leq i \leq D$ indicating the power allocation of the i th D2D pair.

Algorithm 4 illustrates the DE based power allocation for D2D pairs, the whole procedures are similar as that in algorithm 1, the main differences are that we first use the RB assignment as the input, and we also take algorithm 2 to find the optimal power allocation of NOMA CUES in correspondence with the D2D power allocation.

Remark 3: The time complexity of algorithm 4 is similar as that of algorithm 1. The only difference is that the time complexity of algorithm 2 should also be considered. Let $O(f)$ be the complexity of fitness evaluation, and $O(P)$ be the complexity of algorithm 2, the complexity of algorithm 3 is $O(TQ(O(f) + Q + O(P)))$.

C. JOINT OPTIMIZATION FOR BOTH RB ASSIGNMENT AND POWER ALLOCATION

With the proposed DE based RB assignment and power allocation algorithm, we further propose a joint optimization algorithm to maximize the D2D transmission rate, as shown in Algorithm 5. The first step is power initialization, where the BS allocates a random and feasible allocation P_n^m for each CUE, and each D2D pair selects the maximum power as its power allocation. In the second step, the DE based RB assignment is first performed based on the current power allocation. Subsequently, the power allocation algorithm either with SCA or DE is executed based on the sub-channel assignment result. This process is repeated until the maximum number of i_{max} iterations or meets the termination condition, where the joint solution including the RB assignment, power allocation and NOMA decoding order is obtained.

Theorem 4: The proposed joint optimization algorithm is guaranteed to converge.

Proof: Each iteration of the joint optimization algorithm contains two main procedures: DE based RB assignment, and power allocation either with DE or SCA. Since the obtained objective value is guaranteed to not decrease in each procedure, and the upper bound of the objective value exists due to the limited resources. We can conclude that

Algorithm 4 D2D Power Allocation Based on DE

Input: The maximum iteration T , the RB assignment of D2D pairs $\{v_d^m | \forall d \in \mathcal{D}\}$ and the RB assignment of CUEs $\{v_n^m | \forall n \in \mathcal{N}\}$

Output: the power allocation of D2D pairs

$\{P_d^m | \forall d \in \mathcal{D}\}$

Set $t = 1$

Generate initiation population \mathcal{Q} according to the designed encoding scheme

Calculate the power allocation $\{P_n^m | \forall n \in \mathcal{N}\}$ for each individual in \mathcal{Q} with $\{P_d^m | \forall d \in \mathcal{D}\}$, $\{v_d^m | \forall d \in \mathcal{D}\}$ and $\{v_n^m | \forall n \in \mathcal{N}\}$ using algorithm 2

Calculate the fitness value for each individual in \mathcal{Q} with $\{P_n^m | \forall n \in \mathcal{N}\}$, $\{P_d^m | \forall d \in \mathcal{D}\}$, $\{v_d^m | \forall d \in \mathcal{D}\}$ and $\{v_n^m | \forall n \in \mathcal{N}\}$

while $t \leq T$ **do**

Set $\mathcal{Q}' = \Phi$ and $i = 1$

while $i \leq Q$ **do**

Randomly select three individuals Γ^l , Γ^c , and Γ^u from \mathcal{Q} and sorting them such that $f_l \leq f_c \leq f_u$

Perform mutation operation to generate a individual Γ_t^i according according (11)

Calculate the crossover probability cr_i according to (13)

Crossover Γ_t^i with Γ^i with the probability cr_i

$\mathcal{Q}' = \mathcal{Q}' \cup \{\Gamma_t^i\}$

Calculate the power allocation $\{P_n^m | \forall n \in \mathcal{N}\}$ with $\{P_d^m | \forall d \in \mathcal{D}\}$ represented in Γ_t^i using algorithm 2

Calculate the fitness value for individual Γ_t^i with $\{P_n^m | \forall n \in \mathcal{N}\}$, $\{P_d^m | \forall d \in \mathcal{D}\}$, $\{v_d^m | \forall d \in \mathcal{D}\}$ and $\{v_n^m | \forall n \in \mathcal{N}\}$

$i = i + 1$

end

$t = t + 1$

Replace the individuals with low fitness values in population \mathcal{Q} with the children in offspring \mathcal{Q}'

end

Return the fittest individual in \mathcal{Q}

the joint optimization converges within limited number of iterations. \square

Remark 4: The computational complexity of the joint optimization is determined by the complexity of DE based RB assignment and power allocation. Specifically, this algorithm includes two looped operations: the inner loop of DE based optimization and the outer loop of the joint optimization. Let K as the maximum number of iteration of the outer loop, O_1 as the time complexity of algorithm 1, and O_3 as the time complexity of power allocation, the complexity of this joint optimization is $O(K(O_1 + O_3))$.

VI. NUMERICAL RESULTS

In this section, we provide numerical results to illustrate the performance of our proposed algorithm. We consider

Algorithm 5 Joint Optimization on RB Assignment and Power Allocation

Initialization

Set $P_d = P_d^{max}$ ($\forall d \in \mathcal{D}$), and $P_n^m = \frac{P_b^{max}}{NM}$

($\forall n \in \mathcal{N}, \forall m \in \mathcal{M}$)

set $i = 0$
while $i \leq K$ **and** $convergence = False$ **do**

Applying DE-based RB assignment to update $\{v_n^m | \forall n \in \mathcal{N}\}$ and $\{v_d^m | \forall d \in \mathcal{D}\}$ with current $\{P_n^m | \forall n \in \mathcal{N}\}$ and $\{P_d^m | \forall d \in \mathcal{D}\}$

Applying the power allocation either with

SCA or DE to update $\{P_n^m | \forall n \in \mathcal{N}\}$ and $\{P_d^m | \forall d \in \mathcal{D}\}$ with current $\{v_n^m | \forall n \in \mathcal{N}\}$ and $\{v_d^m | \forall d \in \mathcal{D}\}$
if $|f(i) - f(i-1)| \geq T_{th}$ **then**

| $convergence = False$
else

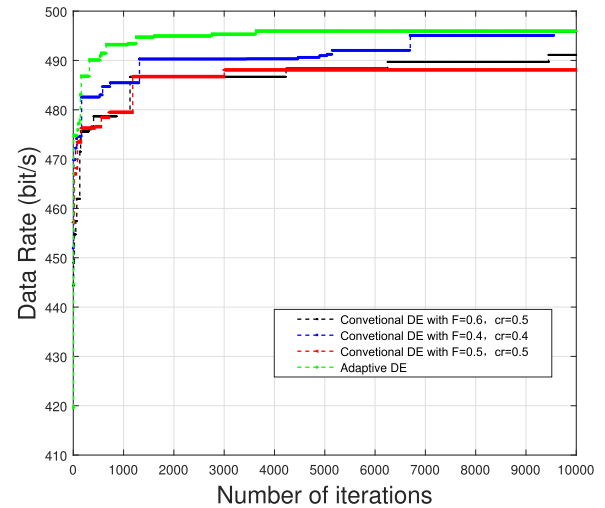
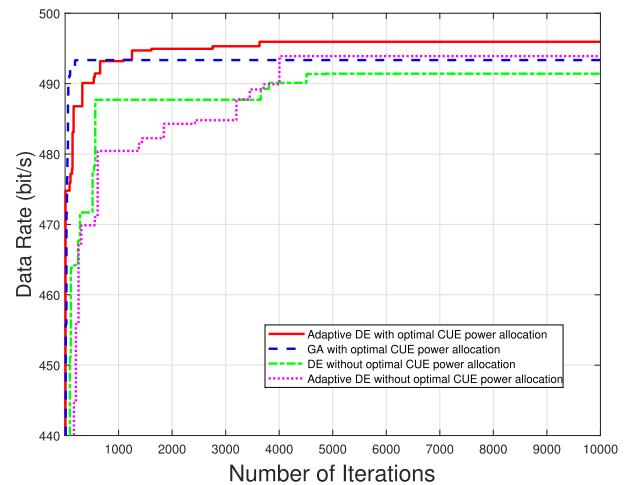
| $convergence = True$
end
 $i = i + 1$
end
TABLE 1. Simulation parameters.

Parameter	Value
The maximum number of CUEs N	10
Maximum transmit power of the BS	43dBm
Maximum transmit power of D2D pairs	10dBm
Coverage range of the BS	500m
Maximum D2D transmission range	50m
Noise PSD	-174dBm
Population size	100
Maximum iteration of DE	10000

a D2D enabled cellular network with no more than 10 CUEs and no more than 15 D2D pairs. The details of parameters are summarized in Table 1 unless otherwise specified. The corresponding simulations are implemented in Matlab 2014a in a laptop with Intel (i5-4300) CPU. All the results are obtained by averaging 100 simulations.

We first test the performance the convergence behavior of our algorithm. Note that the convergence behavior of DE is affected by many factors, such as the diversity of the initial population, mutation probability, crossover mechanism, etc.. Besides that, for DE algorithm with integer encoding scheme, whether there exists the convergence is still an open problem [29]. Similar as that in [30], extensive simulations are employed to look at the convergence issue. In our simulations, we set the maximum number of generation as 10000. Actually, the number of generations required for convergence depends on the size of population and the length of the individual. For example, more generations are needed for systems with large scale of the problem space, i.e. larger number of CUEs or D2D pairs or more RBs.

Fig. 3 plots the convergence behavior of DEs with fixed parameters. Fig. 4 plots the convergence behavior comparison of algorithms with and without power allocation.


FIGURE 3. Convergence behavior comparison with DEs using fixed parameters.

FIGURE 4. Convergence behavior comparison with algorithms using fixed power allocation.

From Fig. 3 and 4, we can observe that the algorithm converge after approximately 4000. And in our computer, it takes 120 seconds to converge. This is sufficient for many applications. If we use a more powerful computer, it is expected that it can converge much faster. From Fig. 3, we observe that our algorithm outperform conventional DE with fixed evolution parameters, which testify that the effectiveness of the self-adaptive mechanism. From Fig. 4, we also observe that by apply the algorithm 2 in finding the optimal CUE power allocation in correspondence with D2D power allocation, we obtain a much better performance than with fixed power allocation. Besides that, we also compare the performance of DE with GA with the same setting, and we observe that although GA converges much faster than DE, DE outperforms GA in searching the optimal solution.

We then test the performance of our algorithm with conventional OMA technology. Fig. 5 plots the data rate of D2D pairs versus different number of D2D pairs with different technology. As expected, by using NOMA technology

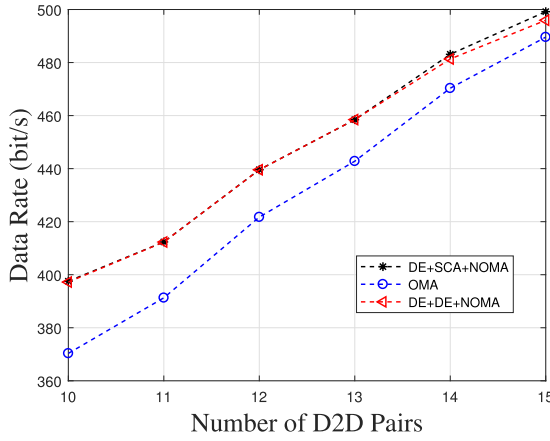


FIGURE 5. Performance comparison versus different number of D2D pairs.

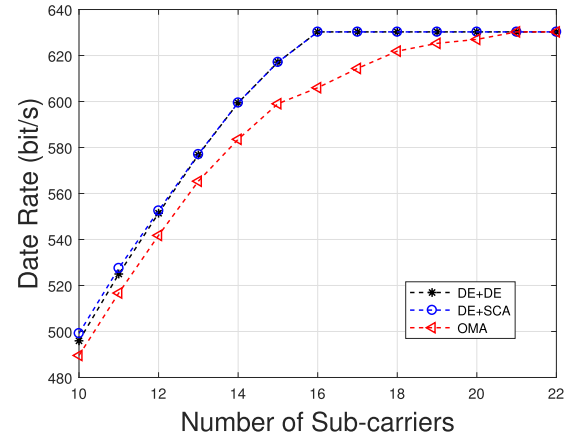


FIGURE 7. Performance comparison versus different number of RBs.

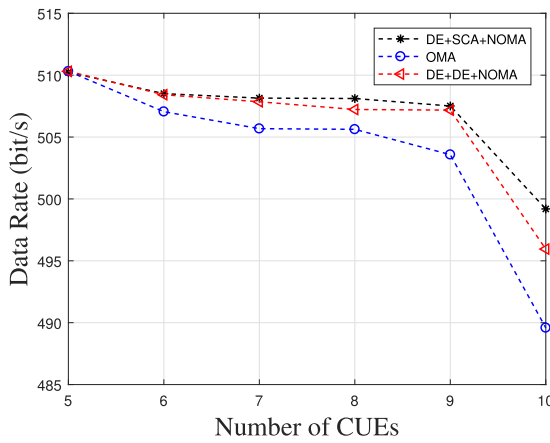


FIGURE 6. Performance comparison versus different number of CUEs.

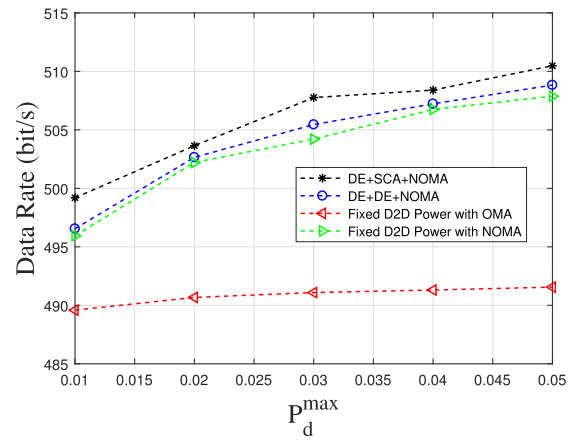


FIGURE 8. Energy efficiency versus different number of UEs.

on the CUEs, a higher D2D data rate is obtained compared with that using OMA technology. We also observe that DE with SCA based power allocation has a very similar performance with that with DE based power allocation, which also testify the effectiveness of DE in finding the optimal solution. We also note that the data rate obtained by NOMA or OMA technology increases with increasing the number of D2D pairs. However, when the number of D2D pairs is large, the increasing speed is lower than that with OMA technology. This is mainly because that NOMA technology helps CUE to take the same RB, more RBs are available for D2D pairs. Additionally, the interference generated by NOMA CUEs is also reduced, thus a much higher data rate is obtained.

We further test the performance of our algorithm with different number of CUEs and different number of RBs. Fig. 6 plots the data rate versus different number of CUEs. It is shown that the data rate decreasing with increasing the number of CUEs, and our algorithm outperforms that with OMA technology. We also observe that the decreasing speed of our algorithm is much smaller than that with OMA technology, which testify that our algorithm performs much better in networks with small resources. Fig. 7 plots the data rate versus different number of RBs. It is shown that the data

rate decreasing with increasing the number of RBs, and our algorithm outperforms that with OMA technology. We also observe that the increasing speed of our algorithm is much smaller than that with OMA technology, which is mainly because that when a network has a larger number of RBs, both CUEs and D2D pairs will take a unique RB, thus the same performance is obtained.

We finally compare the algorithm with algorithms without power allocation optimization. For those algorithms without D2D power allocation optimization, we assume all D2D pairs using the maximum powers. Fig. 8 and Fig. 9 respectively illustrate the performance in terms of data rate and energy efficiency for different P_d^{max} . It is shown that the performance increases with increasing the P_d^{max} . We also notice that optimization on D2D power allocation obtains the highest data rate and the energy efficiency than that with fixed power allocation or OMA technology. This can be explained by the fact that increasing the maximum allocated power increases the potential gain from the spectral diversity of NOMA, and thus much more data rate is occurred. However, due to the fact that there is no power allocation optimization on the D2D transmission with the maximum power, it achieves the minimum energy efficiency compared with the other algorithms.

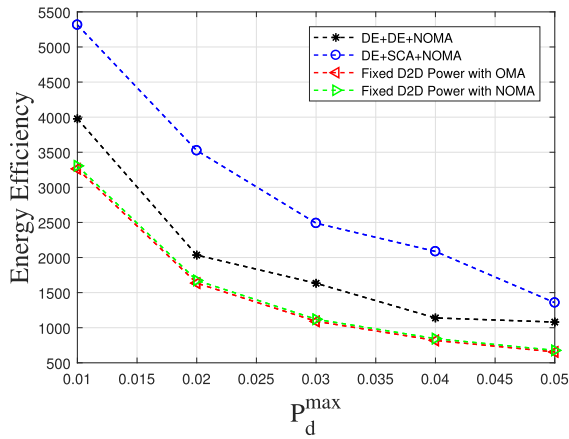


FIGURE 9. Energy efficiency versus different number of UEs.

VII. CONCLUSIONS

In this paper, we have presented the joint optimization algorithms to achieve a high data rate for D2D pairs in a NOMA enabled cellular network. We have formulated a joint resource allocation problem taking into account the NOMA clustering, RB assignment and power allocation. To solve this optimization problem, we have proposed DDM framework to decouple it into two sub-problems. For the RB assignment problem, we have proposed a non-convex optimization method based on DE to find the optimal RB assignment with given power allocation. For the power allocation problem, we have proposed a heuristic algorithm to find the optimal power allocation for CUEs with given D2D power allocation. We further have applied SCA method to find the joint resource allocation for both D2D pairs and CUEs. Numerical results show that our method is effective in maximizing the data rate for D2D pairs, and outperforms conventional OMA technology. Its performance is increased by adding more RBs or increasing the allocated power.

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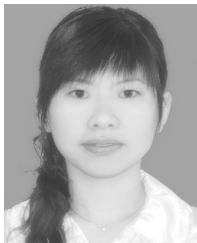
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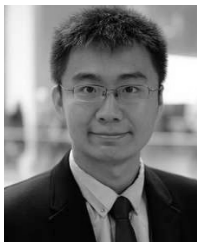


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